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OPTIMAL VALUE ESTIMATION APPLIED
TO THE REDISTRICTING PROBLEM

A THESIS

Presented to
The Faculty of the Graduate Division
by
William Walter Swart

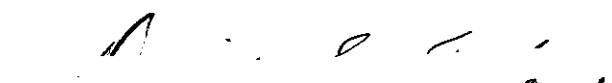
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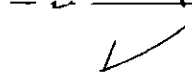
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SUMMARY

This thesis develops a procedure that may be used to estimate the objective function value of the optimal solution to an optimization problem. The only requirement for the procedure to be applicable is that it be practical to obtain feasible solutions to the optimization problem.

The approach consists of investigating the distribution of feasible solution to the problem and using statistical procedures to estimate a bound on the range of feasible solutions. This bound is then taken as an estimate of the optimal solution to the problem.

The procedure is developed for and applied to the redistricting problem as formulated by Weaver and Hess (4). A generalized algorithm is presented in Appendix I.

One item of particular interest in this thesis is the use of a heretofore largely neglected method of parameter estimation--that of estimating the parameters of the population distribution which characterize a set of data by minimizing the test statistic of the chi-square goodness-of-fit test.

Listings of the computer programs used for this research are included in Appendix II.

CHAPTER I

INTRODUCTION

General

Decision problems arise in many fields. Typically, such problems require that decision variables satisfy certain constraints which are imposed by the problem situation. Depending on the constraint set, there may be several feasible choices for the decision variables. As a result, the decision-maker must seek the best set of decision variables which satisfy the constraints. The term "best" is relative and implies that the decision-maker has a criterion by which to determine the "goodness" of a solution to the problem.

If the criterion and the constraints can be expressed in analytical relationships between the decision variables, then the problem may be formulated as follows:

$$\begin{array}{ll}
 \text{Maximize (Minimize)} & f(X) \\
 \text{over all } x & \\
 \text{Subject to} & g_j(X) \geq 0 \qquad (1.1)
 \end{array}$$

Where:

X is an N -dimensional vector of decision variables.

$f(X)$ is a criterion function expressing a measure of effectiveness of the solution, and

$g_j(X)$ is a M -dimensional constraint set imposed on the problem.

Problems such as (1.1) belong to the general class of constrained optimization problems. Because these problems occur frequently, a great deal of work has been done on methods for their solution. Unfortunately, however, efficient and practical techniques are available only for problems which can be analytically structured to meet some rather stringent conditions. A review and discussion of these may be found in Reference 1.

In realistic situations, the decision-maker must find a solution to a problem even though the analytical formulation does not satisfy the necessary conditions for solution by one of the available techniques. Under such circumstances, it is generally more practical to find a solution that satisfies the constraints of the problem (a feasible solution) than to seek the solution which optimizes the criterion *and* satisfies the constraints simultaneously (the optimal solution).

Whenever it is not practical to find the optimal solution to a problem and the decision-maker must be satisfied with finding a feasible solution to the problem, the question then arises as to how good this feasible solution is with respect to the optimal. In many situations, an answer which is arbitrarily close to the optimum may be accepted as satisfactory. However, before a decision can be made as to when a feasible solution is arbitrarily close to the optimum, the optimum itself must be known or estimated.

Objective and Purpose

The objective of this thesis is to develop a procedure whereby a lower bound on the value of the criterion function of an optimization

problem may be found. The purpose is to provide a standard against which feasible solutions to the problem may be evaluated in terms of their proximity to the estimated lower bound.

Background to the Problem

The research was motivated by a situation encountered by the author during his association with a group of individuals interested in the application of quantitative techniques to the problem of non-partisan redistricting. This group developed an integer programming model as a statement of the redistricting problem. In essence, the model represented a location-allocation problem, the solution of which would give the optimal location of Legislative District centers and allocation of population units to these centers.

The measure of effectiveness of the integer programming model is the sum of the squared distances from each population unit center to the center of the Legislative District center to which it is assigned times the population of the particular population unit. This measure of effectiveness was used because, by minimizing it, the resulting geometrical shape of the Legislative Districts would tend to be compact. The constraints to the integer programming formulation specified the number of Legislative Districts to be formed and required that the Legislative Districts have approximately equal populations.

The integer programming formulation appeared to be a very good model of the redistricting problem. Unfortunately, the dimensionality of the problem was such that it was impractical to find the solution. As a result, efforts were directed toward solving an earlier formulation

of the problem. This formulation differs from the original in that single voters are allocated to a set of specified Legislative District centers. This earlier formulation of the problem falls into the category of allocation problems and can be solved by well-known linear programming algorithms.

The measure of effectiveness of the allocation model is the sum of the squared distances from the center of each population unit times the number of voters of that particular population unit assigned to the Legislative District. The constraint set to this model specifies that the resulting Legislative Districts have population equality.

At this point, it is worthwhile to note that the solution to the allocation problem satisfies the constraints to the location-allocation problem. Therefore, the solutions obtained from the allocation problem are feasible solutions to the location-allocation problem. The problem which remains is that of finding the "best" solution to the location-allocation problem from these feasible solutions.

Motivation for Research

The motivation to work on this particular topic stemmed from the apparent lack of published work on estimating, by some rational means, the optimal objective function value to an optimization problem given that it was not practical to solve it.

The particular application which was considered was the estimation of the objective function value to the optimal solution of the location-allocation problem. This was relevant because redistricting plans obtained by the allocation problem could not be compared to any

standard in order to determine their "goodness" with respect to the best redistricting plan that could be obtained. As a consequence, the procedure followed at that time to obtain redistricting plans was to solve the allocation problem with different sets of Legislative District centers until a particular plan was selected by some arbitrary criteria of "goodness".

With an estimate of the objective function value to the optimal solution of the location-allocation problem, an absolute standard of "goodness" for the solution of the allocation problem would be available, eliminating the need of evaluating these solutions with respect to arbitrary criteria.

Approach

The set of feasible solutions to the location-allocation problem is a subset of the set of solutions to the allocation problem. It was decided, therefore, to investigate the distribution of solutions to the allocation problem and to use statistical procedures to estimate a bound on the optimal solution to the location-allocation problem. This was accomplished by taking sets of random Legislative District locations and solving the allocation problem for each.

The results obtained were classified and a histogram constructed. From the shape of the histogram, it was hypothesized that a Weibull distribution might characterize the population distribution of feasible solutions. Before a statistical test was made on this hypothesis, the parameters of the particular Weibull distribution characterizing the population distribution of feasible solutions were estimated by

minimizing the chi-square test statistic for goodness-of-fit.

With the distribution parameters so estimated, the chi-square goodness-of-fit test was used to test the hypothesis that the population distribution was as specified. If the test resulted in failure to reject the hypothesis, then the assumption was made that, in fact, the population distribution was Weibull.

An estimate of the lower bound on the objective function of the allocation problem was obtained by minimizing the location parameter, denoted by γ , subject to the constraint that the original conclusion that the population distribution was Weibull was not rejected. This value of the location parameter, denoted by γ^* was taken to be a lower bound to the objective function values of the location-allocation problem.

CHAPTER II

LITERATURE SURVEY

The Weaver and Hess Algorithm

The specific problem considered in this thesis was originally stated by Weaver and Hess. This chapter is a development of their published work (4).

Redistricting deals with the problem of establishing boundary lines in a geographical area for the purpose of dividing the area into a set of Legislative Districts, or L.D.'s. Each district is then entitled to political representation in the local government.

In 1962 the U. S. Supreme Court ruled that federal courts must decide constitutional challenges to state legislative representation at the suit of qualified voters who claimed that present reapportionment did not offer them equal opportunities for representation (6). As a result of this ruling, a series of court cases, known as the reapportionment cases (4), resulted in the following requirements to be established for legislative districts:

1. Each legislative district should have substantial population equality.
2. All legislative districts should be contiguous.

Even though no specific meaning was given to the terms "substantial population equality" and "contiguous," they have been interpreted as follows: Substantial population equality implies the

average population per district plus or minus some fraction of this amount. Contiguous means that each district should be a single parcel of land bordering with at least one other district.

Any geographical area may be subdivided into a set of smaller areas, each having associated with it a certain population. Weaver and Hess approached the problem of redistricting by taking such a subdivision of the area to be redistricted and denoting each subdivision by a point. Each point had associated with it the coordinates of the center of the subdivision and its corresponding population. Legislative Districts were then composed by selecting sets of points so that each set represented one Legislative District. The actual subdivision used by Weaver and Hess were Enumeration Districts, henceforth referred to as E.D.'s. An E.D. is a population unit used by the U. S. Census Bureau.

To determine a criterion by which to select the E.D.'s that were to compose each L.D., the main consideration was given to the requirement of contiguity. To facilitate later work, the concept of Compact Legislative Districts was used to express contiguity. Compactness is meant to imply that the geometric shape of the resulting Legislative District is regular. (For example, the most regular or compact geometric shape is a circle.) Therefore, it was conjectured that a compact Legislative District would also be contiguous. To obtain a quantitative measure of compactness, Weaver and Hess used the relation d_{ij}^2 / P_j . The d_{ij} represents the distance between the point representing the j th E.D. and the population center of the i th L.D. P_j represents the population of the j th E.D.

If the assignment of E.D.'s to L.D.'s is made so as to minimize the measure of compactness, the resulting assignment will tend to cluster the E.D.'s assigned to a particular L.D. around the population center of that L.D. The resulting L.D. can then be expected to be compact, although this will not always be the case.

The location of the population centers of the L.D.'s were determined by considering each point representing an E.D. as a possible candidate. The points finally chosen were those that minimized the total measure of compactness.

To account for the requirement of substantial population equality between legislative districts, a constraint was placed on the minimization of the total measure of compactness stating that the population of each district should be plus or minus some fraction of the average overall legislative districts.

To summarize what has been said thus far, Weaver and Hess formulated the redistricting problem so that the solution to it would yield the best possible location of legislative district centers and allocation of enumeration districts to these centers such that the total measure of compactness was minimized. Expressed quantitatively, this formulation is:

$$\text{Minimize } f(X) = \sum_{i=1}^n \sum_{j=1}^n d_{ij}^2 P_j x_{ij}$$

Subject to:

$$\sum_{j=1}^n P_j x_{ij} \leq (P_j)/k(1+a)x_{ii} \quad i = 1,n$$

$$\sum_{j=1}^n P_j x_{ij} \geq (P_j)/k(1-a)x_{ii} \quad i = 1,n$$

$$\sum_{i=1}^n x_{ii} = k$$

$$\sum_{i=1}^n x_{ij} = 1 \quad j = 1,n$$

$$x_{ij} = x_{ij}^2 \Rightarrow x_{ij} = \begin{cases} 0 \\ 1 \end{cases} \quad i = 1,n; \quad j = 1,n$$

Where:

i - index of the ith L.D.

j - index of the jth E.D.

k - number of L.D.'s to be formed.

a - allowable population deviation between L.D.'s expressed as a fraction of the average population between L.D.'s.

n - number of E.D.'s composing area to be redistricted.

d_{ij} - linear distance from the jth E.D. to the population center of the ith L.D.

x_{ij} - zero-one decision variable. It takes on a value of one if the j th E.D. is assigned to the i th L.D., and zero otherwise.

The first two constraint sets indicate that the sum of the populations of the E.D.'s assigned to the i th L.D. should be within the allowable population deviation from the average.

The third constraint specifies the number of L.D.'s that are to be formed. The fourth constraint set specifies that each E.D. may only be assigned to one L.D. The fifth constraint set specifies the nature of the decision variables.

Since, as indicated in Chapter I, this problem is computationally impractical to solve, Weaver and Hess developed another formulation of the problem, the solution of which would yield redistricting plans that satisfied the constraint of substantial population equality and that were compact. In other words, a procedure was developed that yielded feasible, but not necessarily optimal, redistricting plans.

The approach taken to develop a formulation of the problem, the solution of which yielded feasible redistricting plans differed from the original problem in two ways. Instead of considering the allocation of the complete population of an E.D. to one L.D., it considers the allocation of individual members of the E.D. population to L.D.'s. Also, instead of determining the optimal location of L.D. population centers together with the optimal allocation of population to these, it must be given a set of L.D. population centers to which it then optimally allocates the population of the area to be redistricted.

The mathematical formulation of this problem is:

$$\text{Minimize } f(Y) = \sum_{i=1}^k \sum_{j=1}^n d_{ij}^2 y_{ij}$$

$$\text{Subject to: } \sum_{j=1}^n y_{ij} = (\sum_k P_j)/k \quad i = 1, k$$

$$\sum_{i=1}^k y_{ij} = P_j \quad j = 1, n$$

$$y_{ij} \geq 0 \quad i = 1, k; j = 1, n$$

where

i - index of population units.

j - index of Legislative Districts.

k - number of Legislative Districts to be formed.

n - number of population units that compose the area to be redistricted.

y_{ij} - number of voters from the i th population unit assigned to the j th Legislative District.

P_j - population of the j th Legislative District.

Note that the format of this formulation corresponds to a transportation problem.

The decision variable of the feasible solution problem is the quantity y_{ij} . This represents the number of voters from the j th E.D.

assigned to the i th L.D. Even though this decision variable may make the total measure of compactness smaller than if the total population of an E.D. had been assigned to one L.D., the consequences that this may bring about are undesirable. This can be explained by the fact that the redistricting of geographical entities is not static. Generally, periodic redistricting of these entities will be necessary to account for the effects of population trends and changes on the "one man one vote" requirement. As a result, new Legislative District boundaries will have to be established and defined after each redistricting. Without a predetermined system, such as defining various Enumeration Districts as being the boundaries of Legislative Districts, the implementation of the redistricting plans may be extremely difficult.

The constraints to the feasible solution problem specify that each Legislative District should have the same population. Since the requirements set up by the Supreme Court are not this stringent, Weaver and Hess formulated a heuristic procedure which attempts to better the solution obtained by the feasible solution problem. The basic idea of the procedure is to take all the E.D.'s that do not have all their population assigned to one L.D. and assign all the population of that E.D. to the L.D. which, in the solution to the feasible solution problem, had the most population of the E.D. assigned to it. Once this was done, the population center of the altered L.D. was recomputed and the feasible solution problem was solved again with the new population centers as data. This process was continued until either a specified number of attempts had been made or the same solution was obtained twice in a row.

In spite of the heuristic procedure, there is no guarantee that the solutions obtained from the feasible solution problem will be optimal. It is possible that by chance the population centers that are given as data to this problem are the same as those that would be given by solution to the original problem. In that case the redistricting plan resulting from the feasible solution problem would be the optimal redistricting plan. Nevertheless, even if this was to occur, there is no way of knowing this. Therefore, it still would be useful to have an estimate of the lower bound on the solution values of the feasible solution problem. This is precisely the purpose of this thesis.

Other

No published work on the subject of optimal value estimation was found. References consulted in conjunction with the various statistical and optimization techniques used are listed in the Bibliography.

CHAPTER III

METHOD OF PROCEDURE

This chapter describes the actual details of the procedure used to estimate a lower bound to the optimal objective function value of the integer-programming formulation of the redistricting problem. The actual data used was obtained from a test problem used by Weaver and Hess (4). The problem was to form five Legislative Districts from a geographical area subdivided into 65 Enumeration Districts.

Obtaining Feasible Solutions

As indicated in Chapter I, a lower bound to the original problem was to be estimated from the population distribution of the results to the feasible solution problem. To estimate this distribution a random sample of 50 solutions to the latter was obtained. This was accomplished by reasoning that if 50 sets of Legislative District population centers selected at random were used as data to this problem, the corresponding solutions would also be random.

To select Legislative District population centers at random, each Enumeration District was identified by an integer number between one and 65. Fifty sets of five different random integers were selected. In each of these 50 sets, the five random integers were taken to represent Enumeration Districts. The geographical location of the population centers of these were used as the locations of the Legislative District population centers.

For each of the 50 sets of random population centers so obtained, the feasible solution problem was solved.

To determine what population distribution could characterize the results listed in Table 1, a histogram of this data, exhibited in Figure 1, was constructed.

Table 1. Results of Feasible Solution Problem for 50 Sets of Legislative District Centers Selected at Random

Class Interval	Class Boundaries	Class Mark	Frequency
1	0.9500 - 1.1640	1.0570	4
2	1.1645 - 1.3780	1.2711	9
3	1.3785 - 1.5920	1.4852	11
4	1.5925 - 1.8060	1.6993	5
5	1.8065 - 2.0200	1.9134	4
6	2.0205 - 2.2340	2.1275	5
7	2.2345 - 2.4480	2.3415	3
8	2.4485 - 2.6620	2.5556	1
9	2.6625 - 2.8760	2.7697	1
10	2.8765 - 3.0900	2.9838	0
11	3.0905 - 3.3050	3.1979	2
12	3.3055 - 3.5190	3.4140	0
13	3.5195 - 3.7330	3.6261	1
14	3.7335 - 3.9470	3.8402	1
15	3.9475 - 4.1610	4.0543	0
16	4.1615 - 4.3750	4.2684	0
17	4.3755 - 4.5890	4.4825	1
18	4.5895 - 4.8030	4.6965	2
19	4.8035 - 5.0170	4.9106	0
20	5.0175 - 5.2310	5.1247	0
21	5.2310 - 5.4450	5.3388	0
22	5.4455 - 5.6600	5.5529	0

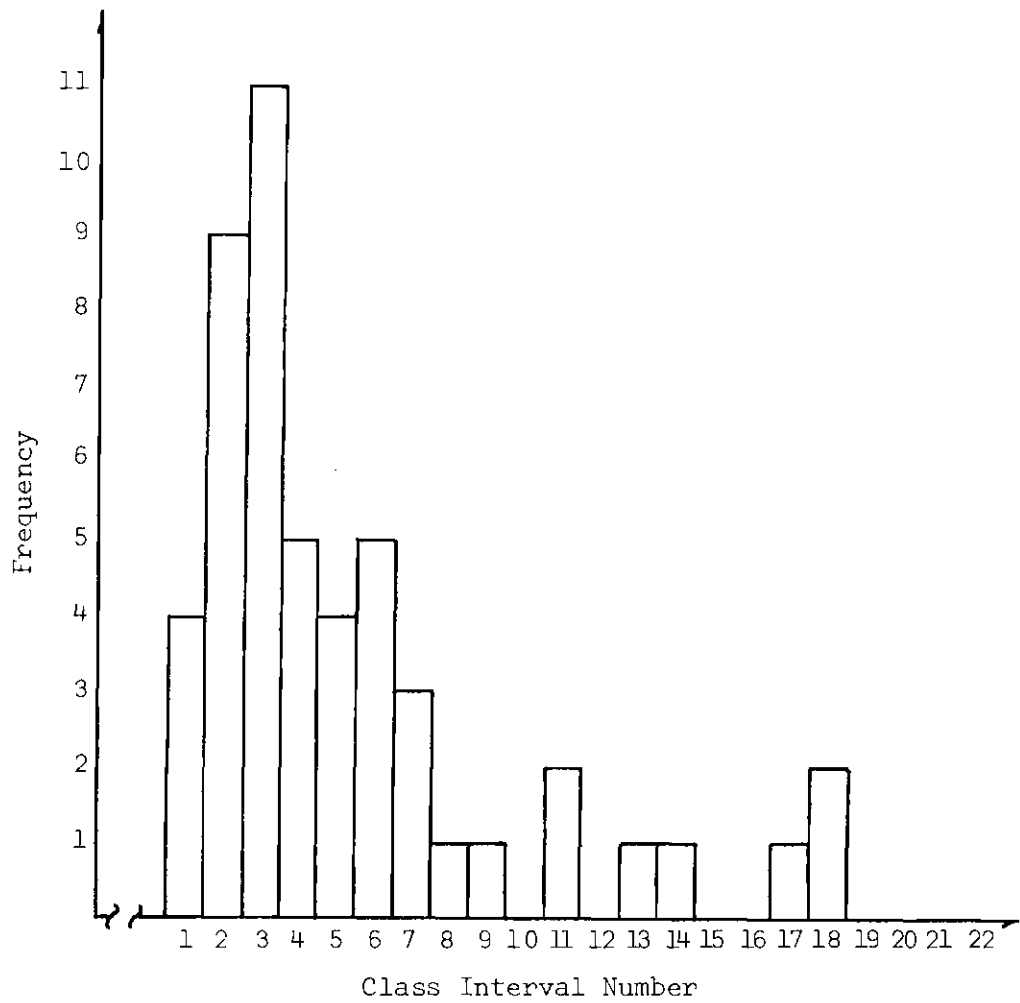


Figure 1. Histogram of Results of Feasible Solution Problem for 50 Sets of Legislative Districts Selected at Random

Fitting a Distribution

The shape of the histogram indicated that a Weibull distribution could be fitted to the data. To check the validity of this assumption the data were plotted on Weibull paper. The results, exhibited in Figure 2, indicated that the assumption was valid.

The parameters of the Weibull distribution fitting the data were estimated so as to minimize the chi-square test statistic, given by:

$$\chi_0^2 = \sum_{i=1}^k \frac{(O_i - nE_i)^2}{nE_i}$$

where:

O_i - actual frequency in i th class interval.

nE_i - expected frequency in i th class interval.

k - number of class intervals.

Although the above-mentioned method of parameter estimation has, to my knowledge, not had wide usage, Fisher (3) has shown that, for large samples, the properties of such estimates are the same as the properties of maximum likelihood estimates.

In addition to the desirable properties of maximum likelihood estimates obtained by the use of the described estimator, the estimator itself will yield parameters that tend to make the observed and expected frequencies for each class interval the same. This can be seen by observing that the numerator of χ_0^2 is equivalent to the criterion used to estimate parameters by the method of least squares. This tendency

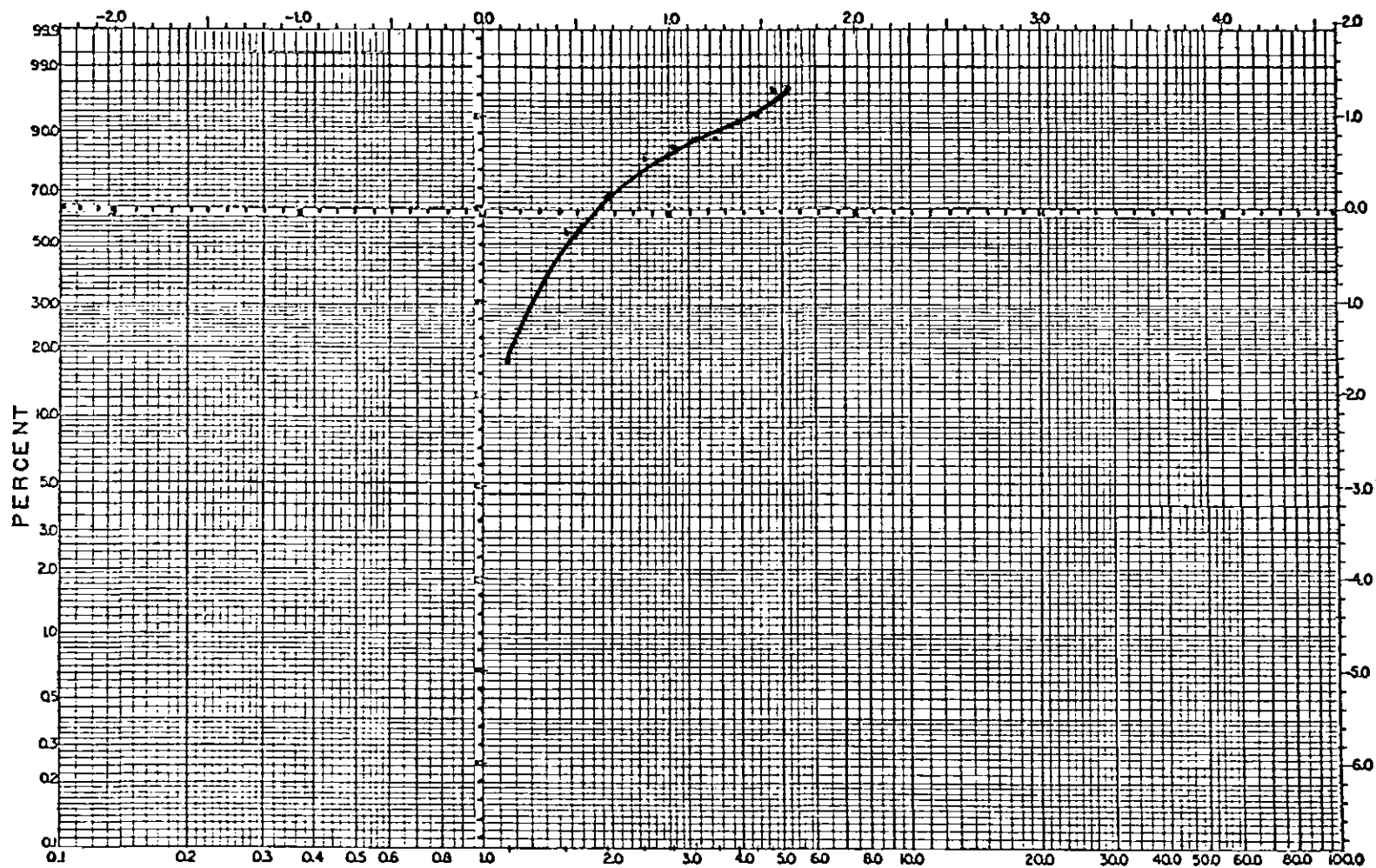


Figure 2. Results of Feasible Solution Problem Plotted on Weibull Paper

Note that by shifting this curve over by approximately one unit the resulting plot is nearly linear. This implies that there is reason to believe that the data are Weibull distributed. For a complete discussion see Reference (2).

of the estimator is very desirable because, theoretically, the chi-square goodness of fit test statistic only has a chi-square distribution when the observed and expected frequencies for each class interval are not significantly different.

The procedure used to minimize χ_0^2 was a directed search method based on the pattern search developed by Hooke and Jeeves (5). Before the minimization was effectuated, the problem was restated as follows:

$$\text{Minimize } \chi_0^2 = \sum_{i=1}^k \frac{\{O_i - n[F(x_i) - F(x_{i-1})]\}^2}{n[F(x_i) - F(x_{i-1})]}$$

$$\text{Subject to: } x_i - \gamma \geq 0 \quad i = 1, k$$

where:

$$F(x_i) = \int_{\gamma}^{x_i} \frac{\beta(x-\gamma)^{\beta-1}}{\alpha} \exp(-(x-\gamma)^{\beta}/\alpha) dx = 1 - \exp(-(x_i - \gamma)^{\beta}/\alpha)$$

x_i - upper limit of the i th class interval.

O_i - observed frequency in i th class interval.

k - number of class intervals.

$$N = \sum_{i=1}^k O_i.$$

α - scale parameter of Weibull Distribution.

β - shape parameter of Weibull Distribution.

γ - location parameter of Weibull Distribution.

The results of this minimization are given in Table 2.

Table 2. Results of Minimizing χ_0^2

Parameters of Weibull Distribution that Minimize χ_0^2 Are:

$$\alpha = 1.117734 \quad \beta = 0.836328 \quad \gamma = 1.008789$$

Objective Function Value is 16.0319101

Class Interval	Observed Frequency	Expected Frequency
1	4.0000000	3.4900647
2	9.0000000	9.4307220
3	11.0000000	6.5597308
4	5.0000000	5.0639477
5	4.0000000	4.0536679
6	5.0000000	3.3110452
7	3.0000000	2.7406773
8	1.0000000	2.2905230
9	1.0000000	1.9285419
10	0.0000000	1.6334396
11	2.0000000	1.3903018
12	0.0000000	1.1882803
13	1.0000000	1.0192556
14	1.0000000	0.8770149
15	0.0000000	0.7567191
16	0.0000000	0.6545450
17	1.0000000	0.5674352
18	2.0000000	0.4929205
19	0.0000000	0.4289892
20	0.0000000	0.3739902
21	0.0000000	0.3265600
22	0.0000000	0.2855654

Goodness of Fit Test

To test whether it was possible to claim that the data came from a population that could be characterized by a Weibull Distribution, the chi-square goodness of fit test was used. The results are exhibited in Table 3.

Table 3. Chi-square Goodness of Fit Test

<i>Null hypothesis:</i>	Empirical data comes from a population distribution that can be characterized by a Weibull distribution with parameters as follows: $\alpha = 1.117734$ $\beta = 0.836328$ $\gamma = 1.008789$
<i>Alternate hypothesis:</i>	Empirical data does not come from a population that can be characterized by the above specified Weibull distribution.
<i>Level of significance:</i>	$\alpha = 0.05$
<i>Nature of experiment:</i>	Random sampling.
<i>Test statistic:</i>	$\chi_0^2 = \sum_{i=1}^k \frac{(O_i - nE_i)^2}{nE_i} = 16.0319101.$
<i>Degrees of freedom:</i>	$V = k - c - 1 = 18.$ c is the number of parameters that were estimated from the data.
<i>Critical value:</i>	$\chi_{\alpha, v}^2 = 28.9.$
<i>Conclusion:</i>	Since $\chi_0^2 < \chi_{\alpha, v}^2$ there is no reason to reject the null hypothesis.

The conclusion from the results of the test indicated that there was no reason to reject the null hypothesis. Although, theoretically, this does not allow us to claim that the data is actually Weibull distributed, the consideration that the null hypothesis would only be rejected at a level of significance below 50 per cent supports, at least

intuitively, the assumption that the data was actually Weibull distributed.

Lower Bound Estimation

Figure 3 shows a plot of the expected frequencies of the fitted distribution superimposed on the original histogram. The location parameter of the fitted distribution indicates where the expected frequencies become greater than zero. The units of the location parameter will be the same as the units of the values of the optimal solutions to the feasible solution algorithm.

A lower bound on the values of the objective function of the feasible solution problem may be defined as the lowest value that the location parameter γ of a Weibull distribution may assume before the hypothesis that the data is Weibull distributed must be rejected. If we denote this value of γ as γ^* , then the above may be restated as:

$$\gamma^* = \underset{\alpha, \beta}{\text{minimum}} \{ \underset{\alpha, \beta}{\text{minimum}} f(\alpha, \beta, \gamma) \}$$

$$\text{Subject to: } \underset{\alpha, \beta}{\text{minimum}} f(\alpha, \beta, \gamma^*) \leq \chi_{\alpha, v}^2$$

where:

$f(\alpha, \beta, \gamma)$ - chi-square test statistic as a function of the parameters α , β , γ .

$f(\alpha, \beta, \gamma^*)$ - Chi-square test statistic as a function of the parameters α and β , γ^* is constant.

$\chi_{\alpha, v}^2$ - critical value of chi-square goodness of fit test.

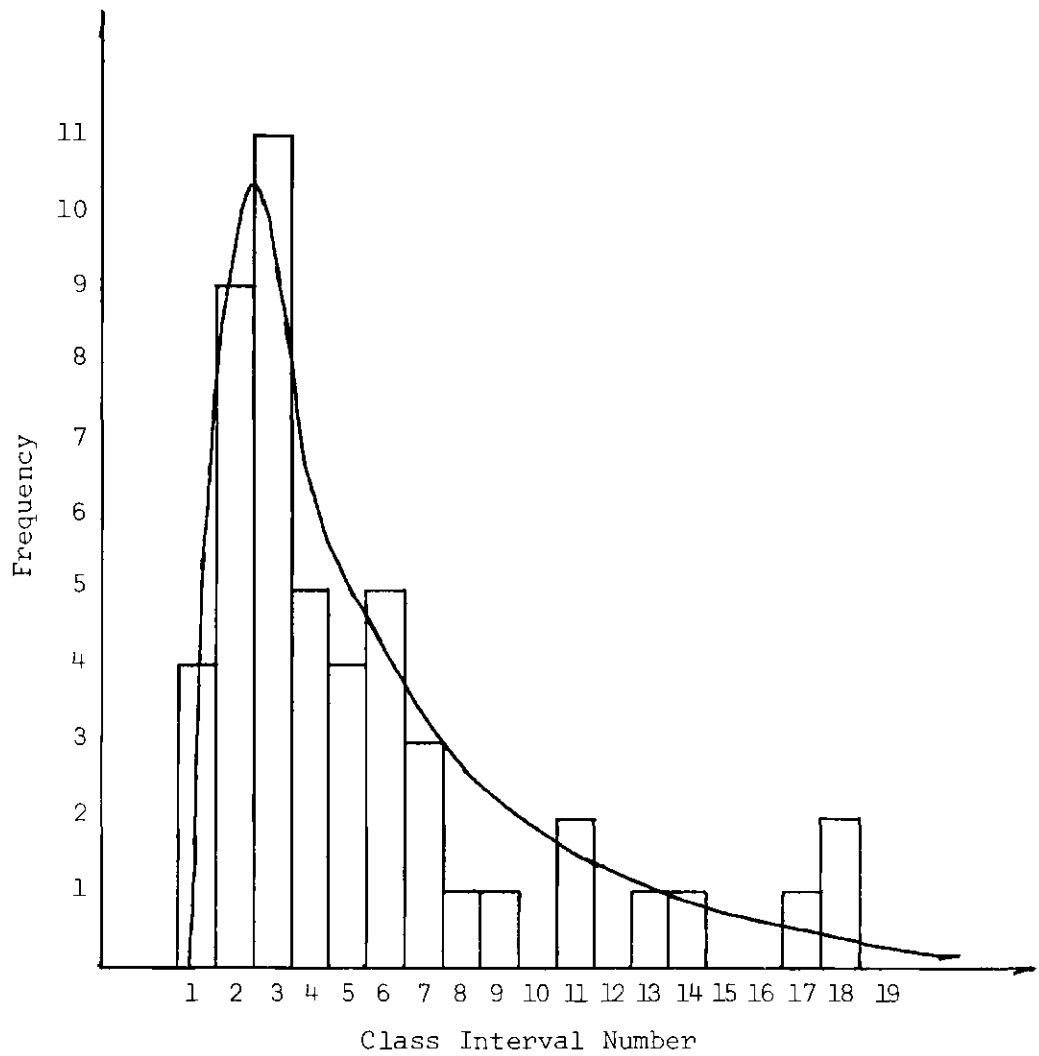


Figure 3. Plot of Actual versus the Expected Frequencies Obtained by Estimating the Parameters of the Weibull Distribution by Minimizing χ^2_0

The above formulation simply states that γ^* is the location parameter of the most extreme Weibull distribution which could fit the data as determined by the chi-square goodness of fit test. By most extreme it is meant that γ^* is the lowest point on the class interval axis from which a Weibull distribution could characterize the population distribution from which the empirical data was obtained.

Since the above interpretation of γ^* implies that the expected frequency of obtaining values of the objective function of the feasible solution algorithm below γ^* is zero, γ^* represents a lower bound on the objective function values of the feasible solution algorithm.

The procedure used to find γ^* is shown in Flowchart form in Figure 4. The initial values of α , β , and γ should be those estimated by minimization of the chi-square test statistic. After each reduction of γ , the parameters α and β should be re-estimated by finding $f^*(\alpha, \beta)$.

This quantity is the objective function value obtained by solving the following problem:

$$\text{Minimize } f(\alpha, \beta) = \sum_{i=1}^k \frac{\{O_i - n[F(X_i) - F(X_{i-1})]\}^2}{n[F(X_i) - F(X_{i-1})]}$$

$$\text{Subject to: } X_i - \gamma \geq 0 \quad i = 1, k$$

where:

$f(\alpha, \beta)$ - chi-square test statistic as a function of the parameters α and β .

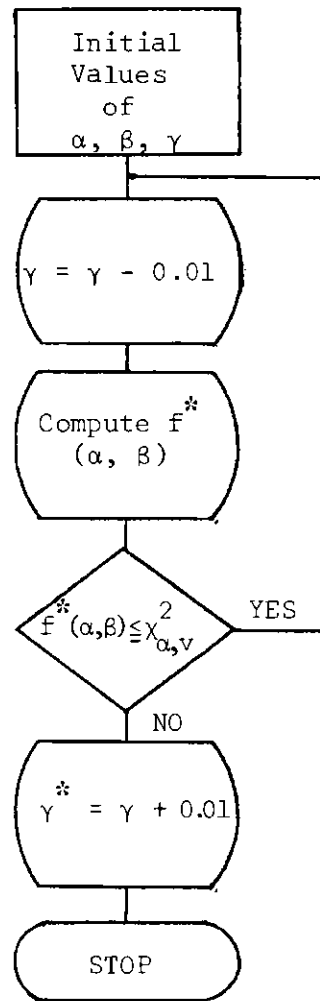


Figure 4. Flowchart of Procedure Followed to Find γ^*

γ - constant.

Other terms - as previously defined.

The conditional block in the flow diagram represents the chi-square goodness of fit test made to determine whether the hypothesis that the population distribution of the data could be considered Weibull with the given parameters. The degrees of freedom for this test, v , are now $k-c$ because the parameter γ is constant and is not estimated from the empirical data.

As soon as the chi-square goodness of fit test results in the rejection of the null hypothesis, the procedure is terminated and γ^* is the last value of γ for which the null hypothesis was not rejected.

The above procedure applied to the test problem yielded a value of γ^* equal to 0.51. This result was obtained by using a level of significance of 5 per cent for the chi-square goodness of fit tests.

CHAPTER IV

CONCLUSIONS AND RECOMMENDATIONS

In the previous chapter a procedure was presented which allowed the estimation of a lower bound to the objective function value of the redistricting problem. The procedure itself consisted of gathering information about the values of the objective function for various initial Legislative District centers and, from this, inferring what the lowest possible objective function value could be. For the particular problem examined, the result appears to be a good estimate of the lower bound, although at this time it is impossible to speculate whether this is a conservative or liberal estimate of the actual solution value.

In addition to the estimation procedure, the minimum chi-square method of parameter estimation appears to hold promise as a fast and efficient estimator. In particular, this method seems to be useful in cases where the maximum likelihood estimates of a distribution are difficult to obtain, but where the properties of such estimates are desirable.

Discussion of the Choice of the Level of Significance

The actual value of γ^* obtained by the procedure described in the previous chapter dependent on the choice of the level of significance used in the chi-square goodness of fit tests. This is so because γ^* will always be the value of the location parameter which makes the value of the chi-square test statistic equal to the critical value of the test.

Since the critical value is dependent on the level of significance used, so is γ^* .

Table 4 exhibits the values of γ^* obtained for various choices of the level of significance.

Table 4. Values of γ^* as a Function of the Level of Significance Used in the Chi-square Goodness of Fit Tests

Level of Significance	γ^*
.25	.80
.10	.65
.05	.51
.01	.27

The interpretation of the relationship between the level of significance used in the chi-square goodness of fit test and the corresponding value of γ^* is not clear. My interpretation is based on the assumption made earlier that the null hypothesis is true if the results of the goodness of fit test failed to reject it. If the null hypothesis is true, then the level of significance indicates the probability of making a Type I error. A Type I error will be made in this case if χ_0^2 is greater than $\chi_{\alpha, v}^2$ because then we have rejected a true hypothesis. Since the relationship between γ and χ_0^2 is such that, as γ decreases χ_0^2 increases, γ^* will be the value of γ that makes the quantity χ_0^2 equal

to $\chi_{\alpha, v}^2$. But, if the null hypothesis is true, then χ_0^2 has a chi-square distribution with v degrees of freedom and the probability that there is a value of γ which makes χ_0^2 greater than $\chi_{\alpha, v}^2$ is α . Therefore, one possible manner in which the level of significance of the chi-squared goodness of fit tests and the corresponding obtained value of γ^* may be related is that α is related to the probability that there is a lower value of the estimate of the lower bound than γ^* .

I would recommend that further research be directed to establishing the exact relationship between the various levels of significance and the corresponding values of γ^* .

Discussion of Data Classification

All the results presented thus far were based on the data being classified into 22 class intervals. Since this was a rather arbitrary selection, the procedure was applied to various classifications of data. Table 5 shows the results obtained.

An analysis of variance was made on these results and the conclusions were that there was a significant difference between the lower bounds obtained for various classifications of the data.

Since there seem to be no good quantitative criteria by which to determine into how many class intervals data should be classified, and since, in this case, the results would have been statistically different, I would recommend that further research be directed to establishing criteria for data classification.

Table 5. Levels of Significance and Lower Bounds
for Various Number of Class Intervals

Number of Class Intervals	.25	.10	.05	.01
10	.36	-	-	-
13	.94	.84	.77	.61
16	.88	.78	.71	.53
19	.95	.85	.78	.62
22	.80	.65	.54	.27
25	.88	.76	.67	.48
28	.91	.76	.66	.41
31	.96	.82	.72	.49

APPENDIX I

APPENDIX I

ALGORITHM FOR ESTIMATING THE OPTIMAL
OBJECTIVE FUNCTION VALUE OF AN OPTIMIZATION PROBLEM

Consider the problem:

Minimize $f(X)$

Subject to: $g_j(X) \geq 0 \quad j = 1, m$

where:

X - L dimensional vector of decision variables.

$f(X)$ - objective function

$g_j(X)$ - m dimensional constraint set

If the problem is of such nature that it is not practical to find the optimal solution, but if it is practical to obtain and evaluate $f(X)$ for any feasible vector of decision variables X , then an estimate of the optimal value of the objective function may be obtained by the following procedure:

1. Select Z sets of L random numbers. Let each set represent a vector of decision variables, denoted by X .
2. Check each vector obtained in Step One for feasibility. If it is feasible, compute $f(X)$, otherwise discard the vector.

3. Classify the value of $f(X)$ into K intervals and construct a Histogram.

4. Select a probability density function $p[f(X)]$ to characterize the population distribution of the values of $f(X)$. This density function should have a lower bound in the form of a location parameter.

5. Denote the location parameter of $p[f(X)]$ by γ and the remaining parameters by θ_i .

6. Estimate the values of γ and θ_i by minimizing the quantity:

$$\chi_0^2 = \sum_{i=1}^k \frac{(O_i - nE_i)^2}{nE_i}$$

where:

O_i - observed frequency of values of $f(X)$ in the i th class interval.

E_i - probability that $C_i \leq f(X) \leq C_{i+1}$.

C_i - upper limit of i th class interval.

$$n = \sum_{i=1}^k O_i$$

k - number of class intervals.

7. Perform the chi-square goodness of fit test as follows:

Null hypothesis: Population distribution of $f(X)$ may be characterized by $p[f(X)]$ with the parameters estimated in Step 6.

Alternate hypothesis: Population distribution of $f(X)$ may not be characterized by $p[f(X)]$ with the parameters estimated in Step 6:

Degrees of freedom:

$$V = K - C - 1$$

where:

V - degrees of freedom.

K - number of class intervals.

C - number of parameters of $p[f(X)]$.

Conclusions: If $\chi_0^2 \leq \chi_{\alpha, V}^2$ then fail to reject the null hypothesis.
Otherwise reject the null hypothesis.

8. If the conclusion of Step 7 fails to reject the null hypothesis, then an estimate of the objective function value to the optimization problem is given by γ^* , where:

$$\gamma^* = \underset{\gamma}{\text{minimize}} \{ \underset{\theta_i}{\text{minimum}} \chi_0^2(\theta_i) \}$$

where:

$\chi_0^2(\theta_i)$ - the chi-square test statistics as a function of the parameters θ_i .

γ - location parameter of $p[f(X)]$.

9. If the conclusion to Step 7 was to reject the null hypothesis, then a different function $p[f(X)]$ must be considered to represent the population distribution of $f(X)$. With the new $p[f(X)]$ the procedure should be started at Step 5 again.

This algorithm is exhibited in Flowchart form in Figure 5.

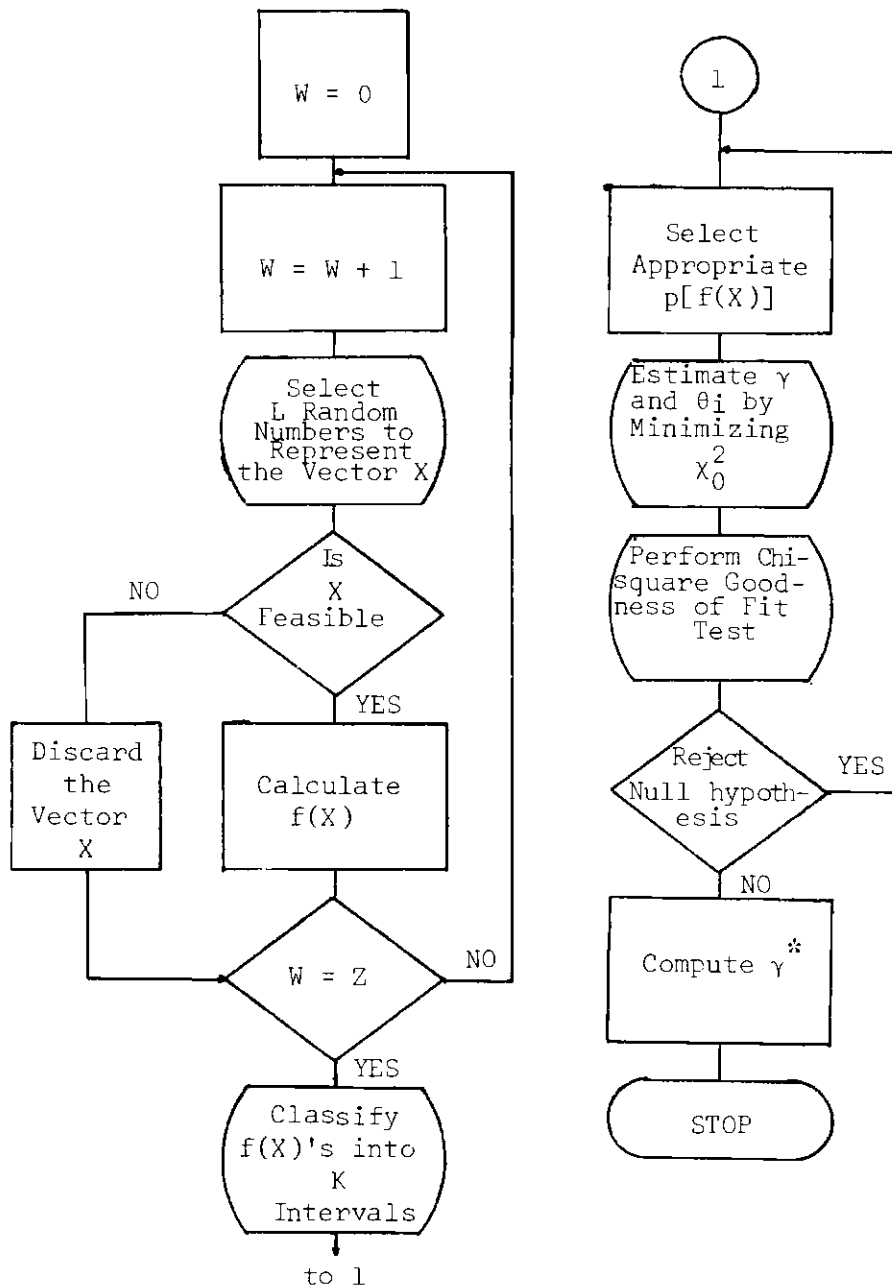


Figure 5. Flowchart of Algorithm to Estimate the Optimal Objective Function Value of an Optimization Problem

APPENDIX II

APPENDIX II

COMPUTER PROGRAM

The following is the listing of the computer program used to:

1. Classify data obtained from the solutions to the allocation problem.
2. Find the parameters of the Weibull Distribution fitting the data by minimizing the chi-square test statistic for goodness of fit.

GEORGIA TECH HECC B-5500 ALGOL COMPILER TUESDAY, 6/13/67, 1:06 AM.

```

BEGIN
    FILE IN CRDS (2,10)
    FILE OUT PRTC 4(2,15)
    FILE OUT NMS 0(2,10)
    INTEGER O,I,MINTER,K,N
    REAL SUM,AVG,DIFF,SS,VAR,SPRDOT,SSUM,DIFF5,RANGE,SPH
    REAL DEL,RHO,DELTA,SPSI,THETA
    REAL KEEP1,KEEP2,KEEP3,KEEP4
    REAL ARRAY T,Z,MID,FREQ(0:100),PHI,PSI(0:10)
    REAL ARRAY X,Y(0:100)
    LIST RADATA(T(1))
    FORMAT FORM1(I2)

    FORMAT FORM2(R8,0)

    FORMAT FORM3(X10,"THE FIRST MOMENT IS",X3,F10,2,/)

    FORMAT FORM4(X10,"THE SECOND MOMENT IS",X3,E20,11,/)

    FORMAT FORM5(X10,"THE STANDARD DEVIATION IS",X3,F10,2,/)

    FORMAT FORM6(///,X10,"SORTED VALUES")

    FORMAT FORM7(///,X10,"INPUT VALUES")

    FORMAT FORM8(X10,"TOTAL IS EQUAL TO",X3,F15,2,/)

PROCEDURE TIEMP
BEGIN
    REAL ARRAY T(0:2)
    FORMAT FMT1(///,"PROCESSOR TIME=",F9,2,/, "I O TIME=",F9,2,/,
        "TOTAL TIME=",F9,2,///)

    T(0)+TIME(2)/60,
    T(1)+TIME(3)/60,
    T(2)+T(0)+T(1)
    WRITE(PRTC,FMT1,T(0),T(1),T(2))
END OF TIEMP

PROCEDURE SORT
BEGIN
    INTEGER IK,KJ
    REAL MAXJ
    FORMAT FORM9(///,X10,"THE RANGE OF THIS DATA IS",X3,F10,2,///)

    FOR IK=1 STEP 1 UNTIL 0 DO
        BEGIN
            0000
            START OF SEGMENT ***** 2
            0000
            0003
            0007
            0010
            0010
            0010
            0010
            0010
            0015
            0017
            0023
            3 IS 4 LONG, NEXT SEG 2
            0023
            4 IS 4 LONG, NEXT SEG 2
            0023
            5 IS 11 LONG, NEXT SEG 2
            0023
            6 IS 11 LONG, NEXT SEG 2
            0023
            7 IS 12 LONG, NEXT SEG 2
            0023
            8 IS 10 LONG, NEXT SEG 2
            0023
            9 IS 9 LONG, NEXT SEG 2
            0023
            10 IS 10 LONG, NEXT SEG 2
            0023
            0023
            0023
            11
            12
            0001
            0001
            0004
            0006
            0008
            0021
            11 IS 25 LONG, NEXT SEG 2
            0023
            0023
            0023
            13
            0000
            0000
            14
            14 IS 16 LONG, NEXT SEG 13
            0000
            0001

```



```

FOR I+1 STEP 1 UNTIL NINTER DO
BEGIN
POINT[I]+POINT[I-1]+INLONG
MID[I]+POINT[I]-INLONG/2
MID[I]+MID[I]/1000000
END;
SSSUM+0;
FOR J+1 STEP 1 UNTIL NINTER DO
BEGIN
IF J=NINTER THEN BEGIN
M+0;
FOR I+1 STEP 1 UNTIL 1 DO
BEGIN
IF Z[I]<POINT[J] AND Z[I]>POINT[J-1] THEN
BEGIN
M+M+1;
VALUR[J,M]+Z[I];
END;
END;
GO TO COST;
END;
M+0;
FOR I+1 STEP 1 UNTIL 1 DO
BEGIN
IF Z[I]<POINT[J] AND Z[I]>POINT[J-1] THEN
BEGIN
M+M+1;
VALUR[J,M]+Z[I];
END;
END;
COSTIMM[J]+M;
FREQ[J]+MM[J];
RLFREQ[J]+MM[J]/0;
SSSUM+SSSUM+RLFREQ[J];
CUFREQ[J]+SSSUM;
END;
WRITE(PRTC,FORM10);
WRITE(PRTC,FORM13);
FOR J+1 STEP 1 UNTIL NINTER DO
BEGIN
WRITE(PRTC,FORM11,POINT[J-1],POINT[J],FREQ[J],RLFREQ[J],
CUFREQ[J]);
LL+MM[J];
FOR I+1 STEP 1 UNTIL LL DO
BEGIN
WRITE(PRTC,FORM12,VALUR[J,I]);
END;
END;
WRITE(PRTC,PAGE1);
WRITE(PRTC,FMT5);
WRITE(WMS,FMT17);
WRITE(WMS,FMT18,NINTER);
FOR I+1 STEP 1 UNTIL NINTER DO
BEGIN
WRITE(PRTC,FMT14,MID[I],RLFREQ[I]);
WRITE(WMS,FMT16,MID[I],RLFREQ[I]);
END;
TIENPD;
WRITE(PRTC,PAGE));
END OF HISTOG;
PROCEDURE DETAIL;

```

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0011
0013
0013
0015
0018
0020
0022
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0025
0025
0026
0027
0028
0028
0031
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0059
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0065
0067
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0077
0081
0082
0083
0083
0091
0093
0095
0098
0101
0104
0112
0113
0113
0122
0132
0134
0135
0137

```

```

15 IS 144 LONG, NEXT SEG 2
0023

```

```

BEGIN
  REAL A,B,G,SUM,ADD,QUAN;
  REAL ARRAY FX(0:100);
  FORMAT FMT1(X30,"WEIRULL EVALUATOR IN CONJUNCTION WITH SEARCH"
    " TECHNIQUES",/,X40,"PARAMETERS ARE: A="F12.6,X2,"B=",
    F12.6,X2,"G="F12.6,/,X10,"INTERVAL",X4,"OBSERVED",
    X4,"EXPECTED",X4,"CHI=SQR.",X4,"CUMM CHI=SQR.",/);
  FORMAT FMT2(X8,I12,A12,7);

  LABEL LBL;
  WRITE(PHTE[PAGE]);
  A=PHI[1];
  B=PHI[2];
  G=PHI[3];
  WRITE(PHTE,FMT1,A,B,G);
  SUM=0;
  FOR I=1 STEP 1 UNTIL N DO
  BEGIN
    FX[I]=1.0-EXP(-(X[I]=G)*B/A);
    ADD=FX[I]-FX[I-1];
    ADD=MAX(ADD,0);
    IF ADD=0 THEN BEGIN
      QUAN=0;
    GO TO LBL;
    END;
    LBL;
    QUAN=(V[I]-ADD)*2/ADD;
    SUM=SUM+QUAN;
    WRITE(PHTE,FMT2,I,Y[I],ADD,QUAN,SUM);
  END;
  TIEMPO;
  END OF DETAIL;

  REAL PROCEDURE EVALUATE(PHI,X,Y,N,K);
  VALUE PHI,X,Y,N,K;
  REAL ARRAY PHT,X,Y(0);
  INTEGER K,N;
  BEGIN
    REAL ARRAY FX(0:100);
    REAL SUM,ADD,QUAN;
    INTEGER I;
    LABEL THREE,THOU,LBL;
    FX[0]=0;
    O=51;
    IF PHI[2]50 THEN GO TO THOU;
    SUM=0;
    IF PHI[3]>2 THEN GO TO THOU;
    FOR I=1 STEP 1 UNTIL N DO
    BEGIN
      QUAN=X[I]-PHT[3];
      IF QUAN<0 THEN
      BEGIN
        THOU;
        EVALUATE+100000;
        GO TO THREE;
      END;
    ELSE

```

```

0023
0023
START OF SEGMENT ***** 25
0000
0001
START OF SEGMENT ***** 26
0001
0001
0001
26 IS 45 LONG, NEXT SEG 25
0001
START OF SEGMENT ***** 27
27 IS 6 LONG, NEXT SEG 25
0001
0001
0004
0005
0006
0007
0018
0019
0020
0020
0025
0028
0029
0030
0031
0033
0033
0033
0035
0036
0050
0052
0053
25 IS 58 LONG, NEXT SEG 2
0023
0023
0023
0023
0023
0023
START OF SEGMENT ***** 28
0001
0001
0001
0001
0003
0003
0005
0006
0007
0009
0009
0010
0011
0012
0012
0012
0015
0015

```

```

        IF PHI(I)=0 THEN GO TO THOU;
        FX(I)+1.0=EXP(-(X(I)-PHI(I)))*PHI(I)/PHI(I));
        ADD*FX(I)=FX(I-1);
        ADD*0*ADD;
        IF ADD=0 THEN GO TO LBL;
        SUM*SUM+(Y(I)-ADD)*2/ADD;
    LBL;
    END;
    EVALUATE*SUM;
THEE;
END OF EVALUATE;

PROCEDURE E;
BEGIN
    FOR I=1 STEP 1 UNTIL K DO
    BEGIN
        PHI(I)*PHI(I)+DEL;
        SPHI*EVALUATE(PHI,X,Y,N,K);
        IF SPHI<SS THEN SS*SPHI ELSE
    BEGIN
        PHI(I)*PHI(I)-2*DEL;
        SPHI*EVALUATE(PHI,X,Y,N,K);
        IF SPHI<SS THEN SS*SPHI ELSE PHI(I)*PHI(I)+DEL;
    END;
    END;
END OF E;
PROCEDURE INPUT;
BEGIN
    FORMAT FMT1(X5,I3,///);

    FORMAT FMT2(X5,P15,6);

    FORMAT FMT3(//,X5,(4,3F15,7,///));

    FORMAT FMT5(X5,F15,7);

    N*INTER;
    FOR I=1 STEP 1 UNTIL N DO
    BEGIN
        X(I)*MJO(I);
        Y(I)*FREQ(I);
    END;
    WRITE(PRTC,FMT1,N);
    FOR I=1 STEP 1 UNTIL N DO
    BEGIN
        WRITE(PRTC,FMT2,X(I),Y(I));
    END;
    WRITE(PRTC,FMT3,K,DEL,RHD,DELTA);
    FOR I=1 STEP 1 UNTIL K DO
    BEGIN
        WRITE(PRTC,FMT5,PSI(I));
    END;
    TIMEPD;
    END OF INPUT;

PROCEDURE OPTIMIZE;
BEGIN

```

0015
0017
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0034
0035
0035
28 IS 41 LONG, NEXT SEG 2
0023
0023
0023
0025
0025
0027
0030
0032
0033
0035
0039
0044
0044
0046
0046
0046
0046
START OF SEGMENT ***** 29
START OF SEGMENT ***** 30
30 IS 7 LONG, NEXT SEG 29
0000
START OF SEGMENT ***** 31
31 IS 5 LONG, NEXT SEG 29
0000
START OF SEGMENT ***** 32
32 IS 10 LONG, NEXT SEG 29
0000
START OF SEGMENT ***** 33
33 IS 5 LONG, NEXT SEG 29
0000
0000
0002
0002
0003
0005
0007
0015
0016
0016
0025
0027
0039
0040
0040
0048
0050
0051
29 IS 52 LONG, NEXT SEG 2
0046
0046

```

COMMENT THIS PROGRAM DOES AN OPTIMUM SEARCH BY THE HOOKE AND JEEVES
PATTERN SEARCH PROCEDURE= WRITTEN BY W W SWART-SPRING 1967
INTEGER NO, I;
LARGFL STANT, ONE, TWO;
FORMAT FMT1(3F12.6, //)
FORMAT FMT4(//)
FORMAT FMT6(///, X30, "PATTERN SEARCH FOR IE 787-WRITTEN BY W W SWART")
)
FORMAT FMT7(X10, "BASE POINT NUMBER", I4, X3, "STEPSIZE", F12.7, //)
FORMAT FMT8(X15, "A=", F12.7, "B=", F12.7, "G=", F12.7, X5, "F(A,B,G)",
F12.7, //)
FORMAT FMT9(//, X10, "EXPLORATORY MOVE RESULTS", //, X15, "A=", F12.7,
"B=", F12.7, "G=", F12.7, X5, "F(A,B,G)", F12.7)
FORMAT FMT10(//, "AFTER", I4, "BASE POINT EXPLORATIONS WE HAVE AT",
"LEAST A LOCAL OPTIMUM LOCATED AT", //, X5, "A=", F12.7,
"B=", F12.7, "G=", F12.7, "WITH MINIMUM VALUE OF F(A,B,G)",
"=", F12.7)
FORMAT FMT12(3(F12.7, ", "))
INPUT
NO=0;
WRITE(PNTR, (PAGE));
WRITE(PNTR, FMT1, PSI(1), PSI(2), PSI(3));
WRITE(PNTR, FMT6);
WRITE(PNTR, FMT4);
START1, SPSI=EVALUATE(PSI, X, Y, N, K);
ONE=SS+SPSI;
COMMENT ESTABLISH BASE POINT;
FOR I=1 STEP 1 UNTIL K DO
BEGIN
PHI(1)=PSI(1)
)
END;
WRITE(PNTR, FMT1, PHI(1), PHI(2), PHI(3));
NO=NO+1;
WRITE(PNTR, FMT7, NO, DEL);
WRITE(PNTR, FMT8, PHI(1), PHI(2), PHI(3), SS);
COMMENT MAKE EXPLORATORY MOVES;
E;
WRITE(PNTR, FMT9, PHI(1), PHI(2), PHI(3), SS);
COMMENT ARE EXPLORATORY MOVES SUCCESSFUL;
IF SS<SPSI THEN
BEGIN
COMMENT IF SUCCESSFUL MAKE PATTERN MOVE;
TWO=FOR I=1 STEP 1 UNTIL K DO
BEGIN
THETA=PSI(1)

```

```

0046
0046
0046
START OF SEGMENT ***** 34
0000
0000
START OF SEGMENT ***** 35
35 IS 5 LONG, NEXT SEG 34
0000
START OF SEGMENT ***** 36
36 IS 5 LONG, NEXT SEG 34
0000
START OF SEGMENT ***** 37
37 IS 15 LONG, NEXT SEG 34
0000
START OF SEGMENT ***** 38
38 IS 14 LONG, NEXT SEG 34
0000
START OF SEGMENT ***** 39
39 IS 15 LONG, NEXT SEG 34
0000
START OF SEGMENT ***** 40
40 IS 21 LONG, NEXT SEG 34
0000
START OF SEGMENT ***** 41
41 IS 34 LONG, NEXT SEG 34
0000
START OF SEGMENT ***** 42
42 IS 7 LONG, NEXT SEG 34
0000
0000
0001
0004
0015
0018
0021
0025
0026
0026
0028
0028
0029
0031
0043
0044
0054
0067
0067
0067
0080
0080
0081
0081
0083
0083

```

```

        PSI[I]+PHI[I]]
        PHI[I]+2*PHI[I]-THETA]
END]
COMMENT END OF PATTERN MOVE, NEW POINT PHI IS THE NEW BASE POINT]
        SPSI+SS]
        SS+SPHI+EVALUATE(PHI,X,Y,N,K)]
COMMENT MAKE EXPLORATORY MOVES]
        NO+NO+1]
        WRITE(PMTC,FMT9,PHI[1],PHI[2],PHI[3],SS)]
E]
COMMENT IF SUCCESSFUL MAKE NEW PATTERN MOVE, OTHERWISE GO TO 1 AND
TRY NEW EXPLORATORY MOVES]
        IF SS<SPSI THEN GO TO TWO ELSE GO TO ONE]
END]
ELSE
COMMENT IF EXPLORATORY MOVES WERE NOT SUCCESSFUL REDUCE STEP SIZE
UNTIL THESE ARE < THAN DELTA]
        IF DEL> DELTA THEN
BEGIN
        DEL+RH0*DEL]
        GO TO ONE]
END]
        WRITE(WMS,FMT12,PHI[1],PHI[2],PHI[3])
        WRITE(PMTC,FMT10,NO,PHI[1],PHI[2],PHI[3],SS)]
TIEMPO]
DETAIL]
END OF OPTIMIZE]

        WRITE(PMTC[N0])
        READ(CRDS,FORM1,0)
        READ(CRDS,FORM1,NINTER)
        READ(CRDS,/,K,DEL,RHO,DELTA)
        FOR I+1 STEP 1 UNTIL K DO
BEGIN
        READ(CRDS,/,PSI[I])
END]
        FOR I+1 STEP 1 UNTIL D DO
BEGIN
        READ(CRDS,FORM2,RAWDATA)
END]
        CLOSE(CRDS,RELEASE)
        SUM+0]
        FOR I+1 STEP 1 UNTIL D DO
BEGIN
        SUM+SUM+T[I]
END]
        AVG+SUM/D]
        SSUM+0]
        FOR I+1 STEP 1 UNTIL D DO
BEGIN
        DIFF+T[I]-AVG]
        DIFFS+DIFF*2]
        SSUM+SSUM+DIFFS]
END]
        VAR+SSUM/(D-1)
        SQROOT+SQRT(VAR)
        WRITE(PMTC,FORM8,SUM)
        WRITE(PMTC,FORM3,AVG)
        WRITE(PMTC,FORM4,VAR)
        WRITE(PMTC,FORM5,SQROOT)
        WRITE(PMTC,FORM7)
        FOR I+1 STEP 1 UNTIL D DO

```

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0126
0140
0140
0141
34 IS 144 LONG, NEXT SEG 2
0046
0049
0057
0065
0077
0079
0079
0087
0090
0091
0091
0092
0097
0098
0099
0101
0101
0102
0104
0106
0106
0108
0108
0109
0110
0112
0114
0116
0117
0125
0133
0141
0149
0152

BEGIN	0153
WRITE(PRTC,FORM2,RAWDATA);	0153
END;	0156
SORT;	0158
KEEP1+PSI[1];	0159
KEEP2+PSI[2];	0160
KEEP3+PSI[3];	0161
KEEP4+DEL;	0162
FOR NINTER+NINTER STEP 3 UNTIL 31 DO	0162
BEGIN	0164
HISTOG;	0164
PSI[1]+KEEP1;	0164
PSI[2]+KEEP2;	0165
PSI[3]+KEEP3;	0167
DEL+KEEP4;	0168
OPTIMIZE;	0169
TIEMPO;	0169
WRITE(PRTC[PAGE]);	0170
END;	0172
END,	0175

2 IS 178 LONG, NEXT SEG 1

EXP IS SEGMENT NUMBER 0043, PRT ADDRESS IS 0136
 LN IS SEGMENT NUMBER 0044, PRT ADDRESS IS 0135
 SORT IS SEGMENT NUMBER 0045, PRT ADDRESS IS 0202
 OUTPUT(W) IS SEGMENT NUMBER 0046, PRT ADDRESS IS 0105
 BLOCK CONTROL IS SEGMENT NUMBER 0047, PRT ADDRESS IS 0005
 INPUT(W) IS SEGMENT NUMBER 0048, PRT ADDRESS IS 0176
 X TO THE I IS SEGMENT NUMBER 0049, PRT ADDRESS IS 0137
 ALGOL WRITE IS SEGMENT NUMBER 0050, PRT ADDRESS IS 0014
 ALGOL READ IS SEGMENT NUMBER 0051, PRT ADDRESS IS 0015
 ALGOL SELECT IS SEGMENT NUMBER 0052, PRT ADDRESS IS 0016

1 IS	2 LONG, NEXT SEG	0
53 IS	69 LONG, NEXT SEG	0

NUMBER OF ERRORS DETECTED = 0. COMPILATION TIME = 59 SECONDS.
 PRT SIZE = 135; TOTAL SEGMENT SIZE = 1159 WORDS; DISK SIZE = 73 SEGS; NO. PGM. SEGS = 53
 ESTIMATED CORE STORAGE REQUIREMENT = 6875 WORDS.

The following is a listing of the
program used to do the operations shown in
Figure 4.

GEORGIA TECH RECC H-5500 ALGOL COMPILER FRI DAY, 6/16/67, 11:22 AM.

```

BEGIN
    COMMENT THIS PROGRAM DOES AN OPTIMUM SEARCH BY THE HODGE AND JEEVES
    PATTERN SEARCH PROCEDURE- WRITTEN BY W M SMART-SPRING 1967
    FILE IN CHR$(2,10)
    FILE OUT MMS 0(2,10)
    FILE OUT PRN1 6(2,15)
    INTEGER NU, T, K, N
    REAL DEL, SP4I, SS, RHO, DELTA, SPST, THETA, U, KEXP
    REAL ARRAY X, Y(0:100), PHI, PSI(0:10), T(0:2)
    REAL ARRAY STOR(0:10)
    LABEL START, UNE, TWO, FINAL, ITER
    FORMAT FMT1(X5, I3, //)

    START OF SEGMENT ***** 2
    10000100 0000
    10000200 0000
    10000300 0000
    10000400 0000
    10000500 0003
    10000600 0007
    10000700 0010
    10000800 0010
    10000900 0010
    10001000 0016
    10001100 0018
    10001200 0018
    3 IS 7 LONG, NEXT SEG 2
    START OF SEGMENT ***** 4
    10001300 0018
    4 IS 5 LONG, NEXT SEG 2
    START OF SEGMENT ***** 5
    10001400 0018
    5 IS 10 LONG, NEXT SEG 2
    START OF SEGMENT ***** 6
    10001500 0018
    6 IS 5 LONG, NEXT SEG 2
    START OF SEGMENT ***** 7
    10001600 0018
    7 IS 5 LONG, NEXT SEG 2
    START OF SEGMENT ***** 8
    10001700 0018
    8 IS 15 LONG, NEXT SEG 2
    START OF SEGMENT ***** 9
    10001800 0018
    9 IS 14 LONG, NEXT SEG 2
    START OF SEGMENT ***** 10
    10001900 0018
    10 IS 15 LONG, NEXT SEG 2
    START OF SEGMENT ***** 11
    10002000 0018
    11 IS 21 LONG, NEXT SEG 2
    START OF SEGMENT ***** 12
    10002100 0018
    12 IS 17 LONG, NEXT SEG 2
    START OF SEGMENT ***** 13
    10002200 0018
    13 IS 7 LONG, NEXT SEG 2
    START OF SEGMENT ***** 14
    10002300 0018
    14 IS 21 LONG, NEXT SEG 14
    START OF SEGMENT ***** 15
    10002400 0018
    15 IS 21 LONG, NEXT SEG 14
    10002500 0018
    10002600 0018
    10002700 0018
    10002800 0018
    10002900 0018
    10003000 0001
    10003100 0001
    10003200 0001
    10003300 0003
    10003400 0005

    FORMAT FMT2(X5, F15, 6)

    FORMAT FMT3(//, X5, I4, 3F15, 7, //)

    FORMAT FMT4(//)

    FORMAT FMT5(X5, F15, 7)

    FORMAT FMT6(//, X30, "PATTERN SEARCH FOR IE 787-WRITTEN BY WM SMART")
    ,
    FORMAT FMT7(X10, "BASE POINT NUMBER", I4, X3, "STEPSIZE", F12, 7, //)

    FORMAT FMT8(X15, "A=", F12, 7, "B=", F12, 7, "C=", F12, 7, X5, "F(A, B, C)=",
    F12, 7, //)

    FORMAT FMT9(//, X10, "EXPLOITORY MOVE RESULTS", //, X15, "A=", F12, 7,
    "B=", F12, 7, "C=", F12, 7, X5, "F(A, B, C)=", F12, 7)

    FORMAT FMT10(X5, "A= ", F12, 7, X3, "B= ", F12, 7, X3, "C= ", F12, 7,
    X5, "MIN F(A, B, C)= ", F12, 7)

    FORMAT FMT11(4(F12, 7, ", ")))

    PROCEDURE TIMEON
    BEGIN
    REAL ARRAY T(0:2)

    FORMAT FMT1(//, "PROCESSOR TIME=", F9, 6, //, "I O TIME=", F9, 6, //,
    "TOTAL TIME=", F12, 6, //)

    T(0)=TIME(2)
    T(1)=TIME(3)
    T(2)=T(0)+T(1)

```



```

      T(0)+T(0)/60,
      T(1)+T(1)/60,
      T(2)+T(2)/60,
      WRITE(PRNT,FMT1,T(0),T(1),T(2))
END OF TIEMPD

PROCEDURE INPUT
  BEGIN
    READ(CRUS,/,N,N)
    FOR I=1 STEP 1 UNTIL N DO
  BEGIN
    READ(CRUS,/,X[I],Y[I])
    Y[I]+Y[I]*D
  END
  READ(CRUS,/,K,DEL,RHD,DELTA)
  FOR I=1 STEP 1 UNTIL K DO
  BEGIN
    READ(CRUS,/,PSI[I])
  END
  WRITE(PRNT,FMT1,N)
  FOR I=1 STEP 1 UNTIL N DO
  BEGIN
    WRITE(PRNT,FMT2,X[I],Y[I])
  END
  WRITE(PRNT,FMT3,K,DEL,RHD,DELTA)
  FOR I=1 STEP 1 UNTIL K DO
  BEGIN
    WRITE(PRNT,FMT5,PSI[I])
  END
END
TIEMPD
  WRITE(PRNT(PAGE))
END OF INPUT
REAL PROCEDURE EVALUATE(PHI,X,Y,N,K)
  VALUE PHI,X,Y,N,K
  REAL ARRAY PHI,X,Y(0)
  INTEGER K,N
  BEGIN
    REAL ARRAY FX(0:100)
    REAL SUM,ADD,QUAN
    INTEGER I
    LABEL THEE,THOU
    IF PHI(1)SO THEN GO TO THOU
    IF PHI(2)SO THEN GO TO THOU
    SUM=0
    FOR I=1 STEP 1 UNTIL N DO
  BEGIN
    QUAN=X(I)-PHI(3)
    IF QUAN<0 THEN
  BEGIN
    THOU
    EVALUATE+100000
    GO TO THEE
  END
  ELSE
    FX(I)+1.0-EXP(-(X(I)-PHI(3))+PHI(2)/PHI(1))
    ADD+FX(I)-FX(I-1)
    ADD+ADD*D
    SUM+SUM+(Y(I)-ADD)*2/ADD
  END
  EVALUATE+SUM
  THEE

```

	10003500	0007	
	10003600	0009	
	10003700	0011	
	10003800	0013	
	10003900	0026	
14 15	30 LONG, NEXT SEG	2	
	10004000	0018	
	10004100	0018	
	10004200	0018	
	10004300	0028	
	10004400	0030	
	10004500	0030	
	10004600	0039	
	10004700	0041	
	10004800	0044	
	10004900	0055	
	10005000	0057	
	10005100	0057	
	10005200	0065	
	10005300	0068	
	10005400	0075	
	10005500	0076	
	10005600	0076	
	10005700	0085	
	10005800	0087	
	10005900	0099	
	10006000	0100	
	10006100	0100	
	10006200	0108	
	10006300	0110	
	10006400	0111	
	10006500	0113	
	10006600	0114	
	10006700	0114	
	10006800	0114	
	10006900	0114	
	10007000	0114	
		0114	
	START OF SEGMENT	*****	16
	10007200	0001	
	10007300	0001	
	10007400	0001	
	10007500	0001	
	10007600	0003	
	10007700	0004	
	10007800	0005	
	10007900	0007	
	10008000	0007	
	10008100	0008	
	10008200	0009	
	10008300	0010	
	10008400	0010	
	10008500	0010	
	10008600	0013	
	10008700	0013	
	10008800	0013	
	10008900	0020	
	10009000	0022	
	10009100	0023	
	10009200	0026	
	10009300	0028	
	10009400	0029	

```

END OF EVALUATE)
PROCEDURE E)
BEGIN
  FOR I=1 STEP 1 UNTIL 2 DO
  BEGIN
    PHI[I]=PHI[I]+DEL;
    SPHI=EVALUATE(PHI,X,Y,N,K);
    IF SPHI<SS THEN SS=SPHI ELSE
  BEGIN
    PHI[I]=PHI[I]-2*DEL;
    SPHI=EVALUATE(PHI,X,Y,N,K);
    IF SPHI<SS THEN SS=SPHI ELSE PHI[I]=PHI[I]+DEL;
  END;
  END;
END OF E)
  WRITE(PHNT[N0]);
  INPUT;
  CLDSE(CNDS,RELEASE);
  KEFP+DEL;
  STOR[1]=PSI[1];
  STOR[2]=PSI[2];
  ITER: IF PSI[1]<0 THEN GO TO FINAL;
  PSI[1]=STOR[1];
  PSI[2]=STOR[2];
  DEL+KEFP;
  NO+0;
  START: SPHI=EVALUATE(PSI,X,Y,N,K);
  ONE=SS+SPSI;
  COMMENT ESTABLISH BASE POINT;
  FOR I=1 STEP 1 UNTIL K DO
  BEGIN
    PHI[I]=PSI[I]
  END;
  NO+NO+1;
  COMMENT MAKE EXPLORATORY MOVES;
  E)
  COMMENT ARE EXPLORATORY MOVES SUCCESSFUL;
  IF SS<SPSI THEN
  BEGIN
    COMMENT IF SUCCESSFUL MAKE PATTERN MOVE;
    TWO: FOR J=1 STEP 1 UNTIL 2 DO
    BEGIN
      THETA=PSI[J];
      PSI[J]=PHI[J];
      PHI[J]=2*PHI[J]-THETA;
    END;
    COMMENT END OF PATTERN MOVE, NEW POINT PHI IS THE NEW BASE POINT;
    SPSI=SS;
    SS+SPHI=EVALUATE(PHI,X,Y,N,K);
    COMMENT MAKE EXPLORATORY MOVES;
    NO+NO+1;
  END;
  COMMENT IF SUCCESSFUL MAKE NEW PATTERN MOVE, OTHERWISE GO TO 1 AND
  TRY NEW EXPLORATORY MOVES;
  IF SS<SPSI THEN GO TO TWO ELSE GO TO ONE;
  END;
  ELSE
  COMMENT IF EXPLORATORY MOVES WERE NOT SUCCESSFUL REDUCE STEP SIZE
  UNTIL THESE ARE < THAN DELTA;
  IF DEL> DELTA THEN
  BEGIN

```

16 IS	10009500	0030	
	36 LONG	NEXT SEG	2
	10009600	0114	
	10009700	0114	
	10009800	0114	
	10009900	0115	
	10010000	0115	
	10010100	0117	
	10010200	0120	
	10010300	0122	
	10010400	0123	
	10010500	0125	
	10010600	0129	
	10010700	0134	
	10010800	0134	
	10010900	0136	
	10011000	0136	
	10011100	0139	
	10011200	0140	
	10011300	0142	
	10011400	0142	
	10011500	0144	
	10011600	0145	
	10011700	0147	
	10011800	0149	
	10011900	0150	
	10012000	0151	
	10012100	0152	
	10012200	0155	
	10012300	0156	
	10012400	0156	
	10012500	0158	
	10012600	0158	
	10012700	0159	
	10012800	0161	
	10012900	0163	
	10013000	0163	
	10013100	0163	
	10013200	0163	
	10013300	0164	
	10013400	0164	
	10013500	0164	
	10013600	0166	
	10013700	0166	
	10013800	0167	
	10013900	0168	
	10014000	0171	
	10014100	0173	
	10014200	0173	
	10014300	0174	
	10014400	0178	
	10014500	0178	
	10014600	0179	
	10014700	0180	
	10014800	0180	
	10014900	0180	
	10015000	0181	
	10015100	0181	
	10015200	0181	
	10015300	0181	
	10015400	0181	
	10015500	0183	

```

      DEL+MMH*DEL;
      GO TO ONE;
END;
      WRITE(PRNT,FMT10,PHI[1],PHI[2],PHI[3],SS);
      WRITE(WWS,FMT11,PHI[1],PHI[2],PHI[3],SS);
      PSI[3]+PSI[3]*.01;
      GO TO ITER;
      FINAL;
      TIEMPO;
END.

```

```

EXP IS SEGMENT NUMBER 0017,PRT ADDRESS IS 0107
LN IS SEGMENT NUMBER 0018,PRT ADDRESS IS 0106
OUTPUT(W) IS SEGMENT NUMBER 0019,PRT ADDRESS IS 0072
BLOCK CONTRL IS SEGMENT NUMBER 0020,PRT ADDRESS IS 0005
INPUT(W) IS SEGMENT NUMBER 0021,PRT ADDRESS IS 0075
X TO THE I IS SEGMENT NUMBER 0022,PRT ADDRESS IS 0110
ALGOL WRITE IS SEGMENT NUMBER 0023,PRT ADDRESS IS 0014
ALGOL READ IS SEGMENT NUMBER 0024,PRT ADDRESS IS 0015
ALGOL SELECT IS SEGMENT NUMBER 0025,PRT ADDRESS IS 0016

```

```

10015600      0183
10015700      0184
10015800      0185
10015900      0185
10016000      0198
10016100      0211
10016200      0213
10016300      0215
10016400      0215
10016500      0215
2 IS 219 LONG, NEXT SEG 1

```

```

1 IS 2 LONG, NEXT SEG 0
26 IS 69 LONG, NEXT SEG 0

```

```

NUMBER OF ERRORS DETECTED = 0. COMPILATION TIME = 16 SECONDS.
PRT SIZE = 76; TOTAL SEGMENT SIZE = 498 WORDS; DISK SIZE = 33 SEGS; NO. PGM. SEGS = 26
ESTIMATED CORE STORAGE REQUIREMENT = 4787 WORDS.

```

The following is a listing of a computer program used to plot the Weibull density function for any given set of parameter values.

END ;	10010900	0168
IF Y[GRAPH]#N THEN	10011000	0168
BEGIN	10011100	0169
IF Y[GRAPH]=0.01 THEN WRITE(MCGOUT,MCG06,MCG01) ;	10011200	0170
IF Y[GRAPH]#0.01 THEN WRITE(MCGOUT[ND],MCG05,MCG03) ;	10011300	0175
END ;	10011400	0180
I + 0 ;	10011500	0180
VARIABLE + VARIABLE+1 ;	10011600	0180
IF VARIABLE=2 THEN	10011700	0182
BEGIN	10011800	0182
FOR XX=1 STEP 5 UNTIL 550 DO	10011900	0183
BEGIN	10012000	0185
X + XX/100 ;	10012100	0185
Y[VARIABLE] + SECFUNC ;	10012200	0186
KEEPEROFYVARIABLE[COUNT+1] + Y[VARIABLE] ;	10012300	0187
IF ABS(Y[GRAPH]-Y[VARIABLE])\$0.005 THEN	10012400	0190
Y[VARIABLE] + Y[GRAPH] ;	10012500	0192
IF Y[GRAPH]=Y[VARIABLE] THEN	10012600	0194
BEGIN	10012700	0195
IF POINT[I] # "*" THEN POINT[I] + "*" ;	10012800	0195
IF POINT[I] = "*" THEN POINT[I] + "X" ;	10012900	0198
COUNT + COUNT+1 ;	10013000	0201
KEEPEROFX[COUNT] + X ;	10013100	0202
KEEPEROFYGRAPH[COUNT] + Y[GRAPH] ;	10013200	0203
END ;	10013300	0205
IF Y[GRAPH]#Y[VARIABLE] THEN	10013400	0205
POINT[I] + " " ;	10013500	0206
I + I+1 ;	10013600	0208
END ;	10013700	0209
VARIABLE + 1 ;	10013800	0211
IF Y[GRAPH] # 0.01 THEN WRITE(MCGOUT,MCG05,MCG03) ;	10013900	0212
END ;	10014000	0217
END ;	10014100	0217
WRITE(MCGOUT[PAGE]);	10014200	0220
FOR I=0 STEP 1 UNTIL COUNT DO	10014300	0222
BEGIN	10014400	0224
MIN+KEEPEROFX[I];	10014500	0224
K+I;	10014600	0225
FOR J=0 STEP 1 UNTIL COUNT DO	10014700	0225
BEGIN	10014800	0227
IF KEEPEROFX[J]<MIN THEN	10014900	0227
BEGIN	10015000	0228
MIN+KEEPEROFX[J];	10015100	0228
K+J;	10015200	0229
END;	10015300	0230
END;	10015400	0230
KK[I]+K;	10015500	0232
RR[K]+KEEPEROFX[K];	10015600	0233
KEEPEROFX[K]+1000000;	10015700	0235
END;	10015800	0236
FOR K=0 STEP 1 UNTIL COUNT DO	10015900	0238
BEGIN	10016000	0241
KEEPEROFX[K]+RR[K];	10016100	0241
END;	10016200	0242
FOR J=0 STEP 1 UNTIL COUNT DO	10016300	0244
BEGIN	10016400	0246
L+KK[J];	10016500	0246
WRITE(MCGOUT,MCG07,KEEPEROFX[L],KEEPEROFYVARIABLE[L],	10016600	0247
KEEPEROFYGRAPH[L]);	10016700	0253
END;	10016800	0258
WRITE(MCGOUT[PAGE]);	10016900	0260
COUNT + COUNT+1 ;	10017000	0263

```

WRITE(MCGOUT,MCGO9,COUNT) ;
WRITE(MCGOUT,FMT1,AA,BB,G,SS);
WRITE(MCGOUT[PAGE]);
JJ+JJ+1;
IF JJ <= NN THEN GO TO ANFANG;
END.

```

```

EXP IS SEGMENT NUMBER 0009,PRT ADDRESS IS 0111
LN IS SEGMENT NUMBER 0010,PRT ADDRESS IS 0110
OUTPUT(W) IS SEGMENT NUMBER 0011,PRT ADDRESS IS 0103
BLOCK CONTROL IS SEGMENT NUMBER 0012,PRT ADDRESS IS 0005
INPUT(W) IS SEGMENT NUMBER 0013,PRT ADDRESS IS 0107
X TO THE I IS SEGMENT NUMBER 0014,PRT ADDRESS IS 0112
GO TO SOLVER IS SEGMENT NUMBER 0015,PRT ADDRESS IS 0106
ALGOL WRITE IS SEGMENT NUMBER 0016,PRT ADDRESS IS 0014
ALGOL READ IS SEGMENT NUMBER 0017,PRT ADDRESS IS 0015
ALGOL SELECT IS SEGMENT NUMBER 0018,PRT ADDRESS IS 0016

```

```

10017100 0264
10017200 0272
10017300 0284
10017400 0287
10017500 0288
10017600 0289
2 IS 293 LONG, NEXT SEG 1

```

```

1 IS 2 LONG, NEXT SEG 0
19 IS 69 LONG, NEXT SEG 0

```

```

NUMBER OF ERRORS DETECTED = 0. COMPILATION TIME = 21 SECONDS.
PRT SIZE = 78; TOTAL SEGMENT SIZE = 437 WORDS; DISK SIZE = 26 SEGS; NO. PGM. SEGS = 19
ESTIMATED CORE STORAGE REQUIREMENT = 4166 WORDS.

```


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